

Examining Emotion Perception in Parkinson's Disease(PD) Patients

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1 Aim

2 Introduction

Parkinson's Disease is a disorder of the central nervous system that affects movements, often including tremors. Smooth muscle movements in the body are due to the chemical messenger that is released in the brain. Nerve cells that release dopamine begin to die. Reduction in the release of dopamine leads to issues in the body movement. The primary symptoms of Parkinson's Disease include tremors, coordination and balance impairments, sleep problems and mood changes.

According to a statistics of 2016, 6.1 million individuals had the disease globally [2]. It is difficult to diagnose the disease when there are no motor or non-motor symptoms. In this direction, we come with a computer aided diagnosis, to facilitate the early detection of the disease. We use the Electroencephalogram (EEG) signals capturing the emotions of Parkinson's disease (PD) patients and normal control (NC) as the dataset to conduct our studies. Details of the data collection protocol are mentioned in Section 4. Electroencephalogram is a test that captures the electrical activity of the brain using headsets which have electrodes attached to the scalp. EEG headsets are used for medical research, analyse the mental states, and to diagnose mental conditions. While there are other tests like Electrocardiogram (ECG), MRI and fMRI to capture the activity of the brain, EEG is cost effective and is known to have high temporal resolution as compared to other techniques, as it can detect changes in brain activity over milliseconds. EEG measures the brain activity directly while other methods record changes in blood flow, metabolic rate, etc.

To analyse these signals, the data is preprocessed which helps remove noise from the data and obtain true neutral signals. Artifacts such as eye blinks and muscle movements tend to contaminate the data. Preprocessing becomes inevitable to reduce the distortion in the signals and to separate the relevant signals from random signals of brain that are picked up from the electrodes [1]. The data preprocessing step is followed by the Feature Extraction process, where Spectral Power Vectors and Common Spatial Patterns are extracted for analysis. Details regarding the feature extraction process are given in Section 4.2.

Machine Learning and Deep Learning leverages computer science algorithms and mathematical techniques to recognise the characteristics of the data, perform classification and make predictions for upcoming events. We employ classical Machine Learning techniques and Neural Networks to classify the data of PD patients and normal control, in terms of emotion perception. The following experiments are performed in this study:

- Binary Classification of PD and NC
- Binary Classification of High Valence (HV) and Low Valence (LV)
- Binary Classification of High Arousal (HA) and Low Arousal (LA)
- Multiclass Categorical Emotion Classification

Binary Classification of PD and NC data is done for the combined data of PD and NC (this is referred as *full* data in the paper), as well as for the data of individual emotions. Binary Classification of HV and LV, Binary Classification of HA and LA and Multiclass Categorical Emotion Classification are performed for the combined data of PD and NC, individually within PD data and individually within NC data.

3 Literature

4 Dataset

The dataset consists of EEG signals of 20 PD (10 males and 10 females), and 20 NC (9 males and 11 females) subjects from Hospital Universiti Kebangsaan Malaysia, Kuala Lumpur, after getting ethical approval from the local ethical committee. EEG data is collected from the subjects using a 14 channel wireless EEG device (Emotiv Epoc Headset) at a sample rate of 128 Hz. Audio-visual

stimuli based data acquisition protocol is designed to acquire EEG data from the subjects over six trials on six emotions. The emotion elicitation protocol is framed by combining the audio (International Affective Digitized Sounds) and visual (International Affective Picture System) databases. The duration of each trial is approximately 4-5 min, and the total time required for each session is about 25 – 30 min. All the subjects are optimally medicated (to reduce the tremor), and were given written consent before participating experiment. The complete details of the data acquisition protocol design, clinical history of PD subjects, ethical approval details, inclusion, and exclusion criteria of PD subjects are given in detail in [5, 4, 3]. The EEG samples collected from the experiment are to further preprocessing.

4.1 Data Preprocessing

The data is preprocessed by applying a thresholding technique to discard the signal amplitudes exceeding $85\mu V$ IIR Bandpass Butterworth filter for signals in the frequency range 8 to 49 Hz.

4.2 Feature Extraction

Spectral Power Vectors

5 Implementation of Classical ML Algorithms

Among the classical Machine Learning algorithms, Naive Bayes, Support Vector Machines, Decision Trees, k -Nearest Neighbors, and Linear Discriminant Analysis are implemented for classification of Spectral, CSP and Raw features.

- k -Nearest Neighbor algorithm works on the principle of similarity between a new data point and the available data points. It puts the new data point to the category that is most similar to the available categories. The parameters considered for tuning of the algorithm include *value of k* , *distance metric* and the *weight function*.
- Support Vector Machine is an algorithm which finds the N -dimensional hyperplane that classifies the data points. The objective is to find the hyperplane that has maximum margin between the classes. The algorithm uses a kernel which transforms the non-separable low-dimensional input data to a higher dimensional space where the data is separable. The

parameters on which tuning is performed are the *kernel* types and C which is the regularisation parameter.

- Gaussian Naive Bayes algorithm is a probabilistic machine learning classification technique based on the Bayes Theorem which assumes independence among the predictors. The algorithm assumes that the presence of a particular feature in one class is unrelated to the presence of features in another class. *Variance* smoothing is a parameter which is tuned in this algorithm.
- Decision Tree is a hierarchical selection algorithm that uses a tree-like graph structure for class separation, where every leaf node represents a category label. The parameters used for tuning the model are *criteria*, which is used to measure the quality of the split and *maximum depth* of the tree.
- Linear Discriminant Analysis is an algorithm which finds linear combinations of features that separate the classes. The *solver* parameter is tuned in the model.

The above algorithms are employed for the classification tasks for the data of Spectral, CSP and the Raw features. The dimensions of the input data are as shown in Table 1. The raw features are standardized onto unit scale ($\mu = 0$, $\sigma = 1$). Principal Component Analysis (PCA) is applied to reduce the data dimensions. The principal components are chosen with 95% of the variance being retained. To find the optimal parameters for the model, an exhaustive Grid Search was performed. Stratified ten fold cross validation was used with a validation split of 90% for training and 10% for testing in all the experiments. The results of the classification are shown in the tables. The metrics used for measuring the performance of the model are accuracy, weighted F-Score and macro F-score. The best performing algorithms are as per the color code.

Features	Dimension	PCA	Dimension after PCA
Spectral	13193×42	No	-
CSP	13193×14	No	-
Raw	13193×8960	Yes	13193×3745

Table 1: Dimension of the features

Table 2 shows the results of binary classification of PD and NC data with the input as combined data and the data of individual emotions, using the ML

Data	Metric	Spectral	CSP	Raw
Full	Macro FScore	0.9672 \pm 0.003	0.8792 \pm 0.0072	0.6589 \pm 0.0115
	Weighted FScore	0.9672 \pm 0.003	0.8791 \pm 0.0072	0.6527 \pm 0.0126
	Accuracy	0.9672 \pm 0.003	0.8792 \pm 0.0072	0.6589 \pm 0.0115
Sad	Macro FScore	0.9726 \pm 0.0127	0.9277 \pm 0.0182	0.6106 \pm 0.0254
	Weighted FScore	0.9726 \pm 0.0128	0.9276 \pm 0.0182	0.6037 \pm 0.0275
	Accuracy	0.9726 \pm 0.0127	0.9277 \pm 0.0182	0.6106 \pm 0.0254
Happy	Macro FScore	0.9664 \pm 0.0121	0.901 \pm 0.0165	0.5861 \pm 0.024
	Weighted FScore	0.9664 \pm 0.0121	0.901 \pm 0.0165	0.586 \pm 0.024
	Accuracy	0.9664 \pm 0.0121	0.901 \pm 0.0165	0.5867 \pm 0.0244
Fear	Macro FScore	0.9642 \pm 0.0125	0.9248 \pm 0.0245	0.6115 \pm 0.0272
	Weighted FScore	0.9642 \pm 0.0126	0.9248 \pm 0.0245	0.6115 \pm 0.0272
	Accuracy	0.9642 \pm 0.0125	0.9248 \pm 0.0245	0.6121 \pm 0.0271
Disgust	Macro FScore	0.9635 \pm 0.0117	0.9038 \pm 0.0282	0.5915 \pm 0.0132
	Weighted FScore	0.9635 \pm 0.0117	0.9037 \pm 0.0282	0.5915 \pm 0.0132
	Accuracy	0.9635 \pm 0.0117	0.9038 \pm 0.0282	0.5923 \pm 0.0131
Surprise	Macro FScore	0.9551 \pm 0.0142	0.9062 \pm 0.022	0.5997 \pm 0.0173
	Weighted FScore	0.9551 \pm 0.0143	0.9062 \pm 0.022	0.5997 \pm 0.0173
	Accuracy	0.9551 \pm 0.0142	0.9062 \pm 0.022	0.6007 \pm 0.017
Anger	Macro FScore	0.9612 \pm 0.0091	0.9206 \pm 0.0199	0.5892 \pm 0.0231
	Weighted FScore	0.9612 \pm 0.0091	0.9205 \pm 0.0199	0.5846 \pm 0.0236
	Accuracy	0.9612 \pm 0.0091	0.9206 \pm 0.0199	0.5892 \pm 0.0231

Table 2: Binary Classification of PD and NC using ML algorithms. Blue, green and red colored text indicates k -NN algorithm, SVM algorithm and Naive Bayes algorithm respectively.

algorithms on the three features. For this experiment, the input is balanced with equal samples in the positive and negative class. We observe that overall, the Spectral features with an accuracy of 0.9672 ± 0.003 outperform CSP features, followed by Raw features in the classification of PD and NC with combined data of PD and NC. Consistent with the trend of full data, spectral features have the highest accuracy, followed by CSP and then Raw features. In the individual emotions, the data of sad emotion has the highest accuracy, followed by the data of anger emotion.

Data	Metric	Spectral	CSP	Raw
Full	Macro FScore	0.7934 \pm 0.009	0.8217 \pm 0.0095	0.6334 \pm 0.0052
	Weighted FScore	0.7787 \pm 0.0106	0.8123 \pm 0.0104	0.5527 \pm 0.0079
	Accuracy	0.7934 \pm 0.009	0.8217 \pm 0.0095	0.6334 \pm 0.0052
PD	Macro FScore	0.7664 \pm 0.0096	0.8506 \pm 0.012	0.6259 \pm 0.0119
	Weighted FScore	0.746 \pm 0.0119	0.8451 \pm 0.0127	0.5548 \pm 0.0122
	Accuracy	0.7664 \pm 0.0096	0.8506 \pm 0.012	0.6259 \pm 0.0119
NC	Macro FScore	0.8189 \pm 0.0174	0.8488 \pm 0.0112	0.636 \pm 0.0103
	Weighted FScore	0.8076 \pm 0.0194	0.847 \pm 0.0118	0.5534 \pm 0.0143
	Accuracy	0.8189 \pm 0.0174	0.8488 \pm 0.0112	0.636 \pm 0.0103

Table 3: Binary Classification of HV and LV using ML algorithms. Blue coloured text indicated k -NN algorithm.

Data	Metric	Spectral	CSP	Raw
Full	Macro FScore	0.9208 \pm 0.0043	0.9336 \pm 0.0048	0.4556 \pm 0.0001
	Weighted FScore	0.9168 \pm 0.0047	0.9316 \pm 0.0052	0.7626 \pm 0.0004
	Accuracy	0.9208 \pm 0.0043	0.9336 \pm 0.0048	0.8369 \pm 0.0003
PD	Macro FScore	0.9298 \pm 0.0075	0.9355 \pm 0.0078	0.8339 \pm 0.0039
	Weighted FScore	0.9256 \pm 0.0087	0.934 \pm 0.0085	0.7653 \pm 0.0046
	Accuracy	0.9298 \pm 0.0075	0.9355 \pm 0.0078	0.8339 \pm 0.0039
NC	Macro FScore	0.9153 \pm 0.0094	0.9434 \pm 0.007	0.8253 \pm 0.003
	Weighted FScore	0.9117 \pm 0.0104	0.9422 \pm 0.0075	0.7618 \pm 0.0041
	Accuracy	0.9153 \pm 0.0094	0.9434 \pm 0.007	0.8253 \pm 0.003

Table 4: Binary Classification of HA and LA using ML algorithms. Blue and red coloured text indicated k -NN algorithm and Naive-Bayes algorithm respectively.

6 Implementation of Deep Convolutional Neural Networks

6.1 1D CNN

6.2 2D CNN

6.3 3D CNN

7 Implementation of Deep Recurrent Neural Networks

8 Discussion

References

- [1] KC Chua et al. "Analysis of epileptic EEG signals using higher order spectra". In: *Journal of medical engineering & technology* 33.1 (2009), pp. 42–50.

Data	Metric	Spectral	CSP	Raw
Full	Macro FScore	0.6408 \pm 0.0101	0.7161 \pm 0.0136	0.1871 \pm 0.0108
	Weighted FScore	0.6401 \pm 0.0101	0.7157 \pm 0.0135	0.1864 \pm 0.0108
	Accuracy	0.6408 \pm 0.0101	0.7161 \pm 0.0136	0.1871 \pm 0.0108
PD	Macro FScore	0.6202 \pm 0.0139	0.7566 \pm 0.0143	0.1661 \pm 0.012
	Weighted FScore	0.6173 \pm 0.0137	0.7564 \pm 0.0144	0.1659 \pm 0.0119
	Accuracy	0.6202 \pm 0.0139	0.7566 \pm 0.0143	0.1817 \pm 0.0111
NC	Macro FScore	0.675 \pm 0.012	0.7373 \pm 0.0125	0.1968 \pm 0.0142
	Weighted FScore	0.6739 \pm 0.0118	0.7365 \pm 0.0127	0.1964 \pm 0.0142
	Accuracy	0.675 \pm 0.012	0.7373 \pm 0.0125	0.1968 \pm 0.0142

Table 5: Categorical emotion classification using ML algorithms. Blue and red coloured text indicated k -NN algorithm and Naive-Bayes algorithm respectively.

- [2] E Ray Dorsey et al. “Global, regional, and national burden of Parkinson’s disease, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016”. In: *The Lancet Neurology* 17.11 (2018), pp. 939–953.
- [3] R Yuvaraj et al. “Brain functional connectivity patterns for emotional state classification in Parkinson’s disease patients without dementia”. In: *Behavioural brain research* 298 (2016), pp. 248–260.
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- [5] Rajamanickam Yuvaraj et al. “Emotion classification in Parkinson’s disease by higher-order spectra and power spectrum features using EEG signals: A comparative study”. In: *Journal of integrative neuroscience* 13.01 (2014), pp. 89–120.